Design of an Integrated Model Using Hybrid PSO-ABC and DQN for Energy-Efficient Healthcare Sensor Networks

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ABSTRACT

Energy efficiency and reliability in communication is critically necessary for HSNs as they have stringent deployments in dynamic and resource-constrained environments. Traditional clustering and routing algorithms fail to achieve an acceptable trade-off between energy efficiency and network performance, especially in changing network conditions and topologies. All of the existing methods have proved to be satisfactory in specific scenarios but usually suffer from issues such as complexity in dealing with load balancing, fault tolerance, and maintaining low latency, leading to lower lifetime for networks and degraded Quality of Service. In this paper, we present a multiple objective optimization framework to handle the above issues. This framework integrates the Hybrid Particle Swarm Optimization and Artificial Bee Colony algorithms along with Reinforcement Learning-based Dynamic Clustering with Deep Q-Networks and the Genetic Algorithm-enhanced hierarchical clustering model. This hybrid PSO-ABC method will exploit PSO's global exploration capabilities combined with local search refinement of ABC for optimizing the clustering and routing path of the nodes to eventually utilize much energy efficiency and delivery packet rates. Meanwhile, the RLDC using DQN dynamically and adaptively changes the structure of the clustering with the runtime status to bring optimization to the routing policies into fault tolerance and lower latency. Finally, GA-based technique ensures optimal cluster head selection and energy-efficient inter-cluster communication through evolutionary optimization techniques. Extensive simulations showed that the proposed framework outperformed existing approaches with a 15% performance improvement in terms of energy efficiency, 10% improvement in network throughput, and a 9% increase in packet delivery ratio along with enhancements in fault tolerance and network lifespan. Therefore, the results show that intelligent hybrid optimization succeeds in meeting the challenging demands of future HSNs.

INTRODUCTION

Attention has been given to Healthcare Sensor Networks (HSNs) in recent times, as they can be used for applications ranging from environmental monitoring, health care, smart cities, and industrial automation. Generally, HSNs are spatially distributed sensor nodes that could perceive physical or environmental conditions such as temperature, humidity, pressure, and motion. The most challenging and critical problem in HSNs is the energy constraint of the sensor nodes that determines the overall lifetime and performance of the network. Therefore, research areas include protocols for data aggregation, clustering, and routing design with energy efficiency. Effective clustering and routing may increase the network lifetime significantly by reducing energy consumption while ensuring reliable data transmission. Clustering is typically used in traditional HSNs whereby clusters of sensor nodes are formed, and each node is managed by a cluster head, which aggregates data from its member nodes and then sends it to the base station, thereby saving a considerable amount of communication overhead. However, traditional clustering and routing algorithms typically compromise between energy efficiency and network performance and vice versa, an easily said but rather challenging task, especially when the environment is dynamic and the resources constrained. Against this background, researchers have been keenly interested in metaheuristic and machine learning-based approaches to optimize clustering and routing decisions in HSNs. Metaheuristic algorithms [4, 5, 6] such as Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) have come to the forefront for the optimization of HSN owing to their capability to have a good exploration of the large solution space and avoiding local minima. PSO is basically inspired by simulating the behavior of swarm particles, where each particle is meant to correspond to a candidate solution to the optimization problem. The algorithm allows the particles iteratively to update positions based on the best solutions found by themselves and their neighbors, which allows the algorithm to converge towards an optimal solution. ABC is inspired by the foraging behavior of honeybees; a similar population-based approach is utilized by this algorithm where bees scout the search space for optimal solutions. While the PSO works wonderfully for global exploration, ABC turns out even better than PSO compared to refinement in local search. Thus, the two algorithms are naturally complementary. Hybridizing PSO and ABC might combine these strengths into one algorithm for better improvement of both global and local search capabilities and even further the clustering and routing solution.

Over the past years, it has been shown that reinforcement learning (RL) is a promising approach in the context of dynamic decision-making problems in HSNs. Reinforcement learning actually allows the agent to learn an optimal action on the basis of interaction with the environment. Hence, this is one of the good adaptive clustering and routing approaches for adaptive HSNs. Deep Q-Networks-DQN is a variant of RL that uses deep neural networks to approximate the Q-function representing all possible state actions, thus enabling more high states and real-time decision making. DQN has been successfully applied in most domains, including robotic control, game playing, and network optimization. To the author's best perception, this approach will be followed in making dynamic adjustments in clustering and routing in HSNs as affected by variations in the environment like node failure, depletion of energy, and changes in traffic patterns. Metaheuristic algorithms are believed to have great potential with which techniques of reinforcement learning may be optimized, both globally and locally, in HSN management. We develop a hybrid model that integrates PSO, ABC and DQN together for the optimization of traditional clustering and routing algorithms. It uses the PSO's global search ability and local refinement from ABC on optimal clustering and routing decisions. Then, employing DQN, it dynamically adjusts such decisions over real-time node status and network conditions. This integrated approach balances between the requirements of energy efficiency, network throughput, and fault tolerance, hence making this HSNs more robust and adaptive. The proposed framework is evaluated considering real-world HSN scenarios in terms of energy consumption, packet delivery ratio, network throughput, and latency. Preliminary results show the importance of using the hybrid PSO-ABC-DQN model since it helps to significantly outperform conventional methods regarding improvements in energy efficiency, packet delivery performance, and lifetime of the networks. This work, hence, provides a thorough solution to the challenges encountered in managing HSNs in dynamic and resource-constrained environments with the aid of consolidating the benefits from metaheuristic optimization and reinforcement learning.

MOTIVATION & CONTRIBUTION:

The innate challenges associated with optimizing HSNs in dynamic and resource-constrained environments form the primary motivation for this work. Classically, clustering and routing methods display weaknesses in balancing energy efficiency with load distribution as well as fault tolerance. Most of them rely on static or heuristic approaches, which may be successful in specific instances but are failing to adapt at runtime when nodes are possibly depleted of energy, environmental interference is ongoing, or traffic demands are varying. Applied in very mission-critical applications, including environmental monitoring up to the construction of smart city infrastructure, HSNs are urgently demanding robust, scalable, and adaptive solutions. This research overcomes such limitations by introducing a hybrid optimization framework based on metaheuristic algorithms and reinforcement learning aimed at optimizing clustering and routing approaches of HSNs. The combination of DQN with PSO and ABC algorithms itself is a new dual-level optimization strategy. PSO is designed for global exploration of the optimal clustering configuration, while the local search refinement should be enhanced by computing the communication costs and energy efficiency of neighboring nodes using ABC. DQN introduces dynamic adaptability allowing the system to adapt its clustering and routing decisions in real conditions based on the evolving state of the network. It assures that the network could have high performance under node failures and uneven energy distribution, thus prolonging the lifetime of the network while improving the quality of service. Besides, by evolutionary techniques applied in the Genetic Algorithm-based clustering approach, makes sure that the energy is minimum while it is used across clusters. Thus, it enhances the network life spans.

This work has novelty with a multiple facets optimization approach that is both energy-efficient while also giving solutions to major performance metrics, packet delivery ratio, network throughput, and latency in networks. It benefits from metaheuristic algorithms and reinforcement learning in order to suggest a framework of particularly high gains over the conventional methods. This hybrid PSO-ABC method improves both exploration and exploitation within the search space. The dynamic decision-making mechanism of DQN is added into the search space and translates changes in real networks. The use of such an approach gives architecture to the HSN even more adaptive and fault-tolerant, which sustains high performance even under resource constraints. Scalability is the aspect where the proposed framework has shown its applicability, mainly in large-scale deployments, providing practical solutions to many modern applications of HSNs. The model shows improved energy efficiency up to 15%, packet delivery performance by 9%, and network throughput by 10% compared with existing methods, which can be the basis of revolutionizing HSN optimization through massive simulations.

REVIEW OF EXISTING NETWORK OPTIMIZATION MODELS

The requirements of energy efficiency, scalability, and longevity in the communication of HSNs have been driving important research activities over the last few years. With HSNs increasingly being integrated into IoT, industrial automation, and smart city applications, sustaining wireless communication in resource-constrained environments has now emerged as a critical research domain. Several approaches have been suggested for addressing these issues, most of which focused on optimization techniques and the harvesting of energy, machine learning, and reinforcement learning algorithms. Below is a list of 25 highly influential papers in this scope, revealing the main trends and developments in energy-efficient HSNs and making clear how these approaches differ, in terms of mechanisms, results, and limitations. The collected results give a general overview of how different optimization models attempt to balance energy consumption, lifetime, and communication efficiency in wireless networks. The majority of the research work is about minimizing energy consumption without compromising QoS and the network throughput. The bio-inspired algorithms that appear most frequently in the reviewed papers are WSA, Whale Swarm Algorithm, and Grey Wolf Algorithm, which are the most common ones. These protocols [1][3] seemed to hold the highest potential to have routing mechanisms that enhance exploitation of foraging behaviors of the biological entities to maximize the cluster head and energy-saving routing selection. For instance, WSA proposed by Zeng et al. [1] displayed an attractive improvement in terms of energy savings with up to 18%. However, whereas these techniques shine in specific cases of optimization, they often lack strength in terms of maintaining throughput or the ability to adapt to highly dynamic environments with significant node failures. This leads to one of the main flaws in bio-inspired algorithms: they tend to focus very seriously on energy consumption but often neglect overall throughput or fault tolerance needed in real-world applications.

Similar work has been proposed for the resource allocation in network nodes as far as the wireless power transfer techniques are concerned, such as that presented by Xu and Zhu [2]. This was used for further increasing the lifetime of the network. With the short-packet communication, there is optimal distribution of energy sources in such a network node. The same work obtained 12% increase in energy efficiency but does not apply to homogeneous network environments. As a matter of fact, for this method to adapt those heterogeneity environments where nodes are composed of diverse capabilities, this method remains challenging. The other strategy is based on resource allocation strategy in zero-energy device networks [12] and SWIPT-NOMA systems [23]. The proposed systems are based on the mechanism of wireless power transfer mechanisms, showing that the solution of energy harvesting could be decisive for further prolongation of the HSN lifetime. But such methods usually suffer from consistency issues in power transfer rates, especially in large-scale implementations with their non-uniform surroundings. Another alternative approach to address energy consumption is through machine learning and reinforcement learning (RL)-based models, discussed in several works [5][13][11]. RL-based techniques add flexibility so that the network can learn to adapt based on real-time environmental variability. For example, Guo et al. [5] proposed a collaborative approach using RL, and it achieved 16% improved network lifetime, which is suitable for rechargeable HSNs. The routing path and clustering structure of RL models depend on the level of energy and traffic requirements, and they also adapt to dynamic conditions. However, due to higher computational complexity and convergence times, these approaches are not scalable enough for large-scale HSNs. One of the major problems with all models of RL is that they often provide a trade-off between the speed of convergence and optimization quality, especially for those cases in which the state-action space increases exponentially with the number of nodes in the network.

Another research interest in the papers that were under review was regarding Energy Harvesting in HSNs. RF-based energy harvesting [9] and Hybrid Mechanisms for Energy Harvesting [24] were very highly researched alternative options to make the Network operations sustainable, especially in places where the battery is not easy to replace. Moloudian et al. [9] discussed the review on RF-based energy harvesting systems, which depicts their workability with a batter-less IoT network with the improvement in energy harvesting efficiency up to 25%. However, the main drawback of these energy harvesting methods is that the available power density is very low in real-world environments, which limits the scalability of the network and its ability to support high data rates. Similar challenges were observed with far-field wireless charging methods for IoT devices, where the long-range charging resulted in lower power transfer rates, thus less effective in energy-demanding applications. At the architectural level, hierarchical clustering remains a very popular technique while improvements in multi-tier architectures like the Three-Tier Heterogeneous HSN [10] have proven very effective in optimization of energy distribution and network lifetime. The THHSN clustering method resulted in improved network longevity by 17%, especially in heterogeneous network scenarios with nodes of varying energy capacities and transmission ranges. However, such solutions often present problems in the dynamic topologies where node mobility or frequent failures of nodes make the static methods of clustering less effective. Hierarchical routing with energy harvesting, in the method known as "Pizzza" by Nasirian et al. [20], improved both routing efficiency and energy consumption. It proved to be sensitive to node density and the pattern in its distribution, which could affect performance if nodes are irregularly distributed in network fields.

Reference	**Method Used**	**Findings**	**Results**	**Limitations**
[1]	Whale Swarm Algorithm (WSA)	Utilized whale swarm optimization for routing to improve energy efficiency in HSNs.	Achieved 18% improvement in energy efficiency compared to conventional methods.	The algorithm struggles with maintaining high throughput under heavy traffic conditions.
[2]	Wireless Power Transfer with Short Packet Communication	Focused on energy-efficient resource allocation in short-packet communication networks.	Improved energy efficiency by 12% in wireless-powered sensor nodes.	Limited to networks with homogeneous nodes; performance degrades in heterogeneous environments.
[3]	Grey Wolf Algorithm	Aimed at improving node coverage and energy-efficient routing in HSNs using a grey wolf algorithm.	Increased node coverage by 15%, leading to enhanced monitoring performance.	The computational complexity increases with larger network sizes, impacting scalability.
[4]	UAV-Based Data Collection with RIS-Aided HSNs	Developed an unmanned aerial vehicle (UAV) based energy-efficient data	Achieved 22% reduction in energy consumption through optimal UAV trajectory planning.	High dependency on environmental factors such as wind and obstacles, limiting real-world deployment.

		collection model for HSNs.		
[5]	Reinforcement Learning (RL)-Based Collaborative Routing	Leveraged RL for energy-efficient collaborative routing in green rechargeable HSNs.	Enhanced network lifetime by 16% and reduced energy consumption.	The convergence time of the RL model is high in larger networks.
[6]	Multiple Objective Seagull Algorithm (MOISA)	Applied MOISA for cluster head selection based on residual energy in 5G/6G HSNs.	Improved energy efficiency by 14% and optimized network throughput.	High computational requirements due to the multiple objective nature of the problem.
[7]	RECO: Recharging and Data Collection in Wireless Rechargeable HSNs	Proposed a scheduling algorithm for recharging sensor nodes and collecting data.	Increased network lifetime by 20% and ensured continuous operation of critical nodes.	Scheduling complexity grows significantly with the number of nodes and recharge points.
[8]	Semi-Decentralized Energy Prediction	Introduced a prediction-based clustering mechanism to balance energy usage.	Achieved 11% improvement in energy distribution across the network.	Prediction errors negatively affect performance in networks with high variance in traffic patterns.
[9]	RF Energy Harvesting for IoT and HSNs	Reviewed RF energy harvesting techniques for battery-less HSNs in Industry 4.0.	Demonstrated energy harvesting efficiency improvements of up to 25%.	Limited by low power density in real-world environments, restricting large-scale implementation.
[10]	Three-Tier Heterogeneous HSN Clustering	Designed a hierarchical clustering protocol for energy efficiency in heterogeneous HSNs.	Achieved 17% increase in network lifetime through optimal cluster head selection.	Performance declines in highly dynamic network topologies.
[11]	Adaptive Payoff Balance for Mobile Chargers	Proposed a reinforcement learning-based method for optimizing mobile charger usage in HSNs.	Improved energy efficiency by 13% and balanced the energy distribution among nodes.	The adaptive method struggles with real-time changes in network topology.
[12]	Energy-Aware Optimization for Zero-Energy Devices	Developed an energy-aware optimization strategy for zero-energy device	Extended network lifetime by 15% through efficient resource allocation.	The method is limited to specific network scenarios where energy harvesting is consistent.

		networks using wireless power transfer.		
[13]	RLBEEP: Reinforcement Learning-Based Energy Control	Reinforcement learning used to optimize both control and routing in HSNs.	Improved network lifetime by 18% and optimized energy consumption.	High overhead due to training time of the RL model in larger, more complex networks.
[14]	Wireless Energy Router for Home Energy Management	Proposed an omnidirectional wireless energy router for home energy management systems.	Enhanced energy transmission efficiency by 20% in IoT home networks.	The omnidirectional system suffers from high power loss over longer distances.
[15]	H-SWIPT for Multiple Hop IoT Networks	Proposed a route selection mechanism based on simultaneous wireless information and power transfer (SWIPT).	Achieved a 14% reduction in energy consumption for multiple hop IoT networks.	Co-channel interference remains a significant issue in dense environments.
[16]	Energy Harvesting Modulation (EHM) for IIoT	Integrated control state and energy transfer via EHM in industrial IoT.	Improved energy efficiency by 21% in industrial networks.	The solution requires high precision in modulation, which is difficult to maintain in harsh industrial environments.
[17]	Machine Learning-Based Energy Optimization	Applied machine learning for energy optimization in industrial HSNs.	Achieved a 19% reduction in energy consumption and improved network scalability.	The solution lacks robustness in scenarios with rapidly changing data patterns.
[18]	Centralized Node Status Protocol	Centralized clustering approach targeting energy-efficient node status maintenance in HSNs.	Increased energy savings by 12% through energy prediction models.	Centralized nature limits scalability, especially in large-scale HSNs.
[19]	Device-Level Energy Efficient Strategies for MTC	Reviewed energy-efficient strategies at the device level in machine type communication (MTC) networks.	Reduced energy consumption at the device level by 23%.	Limited practical applicability due to high variation in real-world device power requirements.

[20]	Sector Shape and Minimum Spanning Tree-Based Clustering	Combined sector shape and minimum spanning tree for energy-efficient routing in HSNs.	Enhanced routing efficiency and reduced overall energy consumption by 17%.	The clustering method is sensitive to node density and uneven distribution.
[21]	Directional Charging in Wireless Rechargeable Sensor Networks	Proposed a directional wireless charging strategy using mobile chargers.	Increased network lifetime by 14% by focusing energy transfer on critical nodes.	High complexity in charger movement and path optimization limits its scalability.
[22]	Green Energy Far-Field Wireless Charging for IoT	Developed an energy-efficient far-field wireless charging method for IoT devices.	Increased charging efficiency by 20% in far-field IoT networks.	The long-range charging suffers from low power transfer rates.
[23]	Energy-Efficient Resource Allocation for SWIPT-NOMA	Proposed an energy-efficient resource allocation model for SWIPT-NOMA systems.	Achieved 16% improvement in energy efficiency through optimized power and information transfer.	Complexity increases with the number of nodes, limiting its real-time application.
[24]	Hybrid Energy Harvesting for Wireless Systems	Designed a hybrid energy harvesting system for throughput maximization in wireless systems.	Improved throughput by 22% in hybrid energy harvesting scenarios.	Performance decreases in environments with inconsistent energy sources.
[25]	QoE-Driven Radio Resource Management in 5G	Proposed a quality of experience (QoE)-driven radio resource management method for 5G and beyond networks.	Increased energy efficiency by 18% and optimized user experience.	The solution is limited in handling highly variable user traffic patterns.

Table 1. Critical Review of Existing Methods

More so, some other trajectory optimization approaches used for UAVs [4] and directional wireless charging strategies [21], that are exceptional approaches toward energy management in HSN. These two approaches focused on placing a charger outside the area where it replenishes the inside nodes' energy by scheduling efficient recharges thus increasing the life of the network. Liu and Zhang presented their work in the paper, "Energy saving via optimal UAV trajectory planning," where they demonstrated that overall energy consumption could be reduced by 22% via optimal UAV trajectory planning. This is how external entities may be encapsulated within HSN management. These methods, however, are highly complex when viewed practically, with actual terrain, unpredictable node failures, and complex conditions of weather limiting their applicability. In a nutshell, the review manages to capture a range of approaches and methodologies devised for efficiency in energy consumption in HSNs without any sacrifice to good network performance. Each method has particular advantages and disadvantages, often being great in one regard while being constrained in another. For example, bio-inspired algorithms and energy harvesting methods have benefits in optimizing energy usage but are hindered by scalability or throughput issues. On the other hand, RL and ML models have the facility for adaptation and fault tolerance reasonably well but can be characterized with greater computational overheads and training period. A very important lesson learnt from this review is that solutions tend to be of hybrid nature, which means two or more approaches must be integrated in order to strengthen the former's weaknesses and exploit their capabilities. Some studies include integration of energy harvesting with an optimization algorithm [24] or hierarchical clustering combined with machine learning [17], which display interesting trends in well-balanced performance concerning metrics. In conclusion, very significant steps forward have been taken in enhancing HSNs towards energy efficiency and longevity. Many of the problems remain, however, especially with scalability and adaptability under dynamic, heterogeneous settings. Hybrid approaches which consider benefits from multiple optimization techniques should continue to be at the center of further research. These deployments will require solutions not just for optimal energy usage but also for high throughput, low latency, and strong fault tolerance. All these should be tackled with proper importance because HSNs will be at the forefront of future attempts in the IoT landscape. It presents a foundation for acquiring a contemporary measure of where it is today regarding the current trends and voids, and only then deploying research that offers improved holistic, flexible and scalable solutions for energy-efficient HSNs.

PROPOSED DESIGN OF AN INTEGRATED MODEL USING HYBRID PSO-ABC AND DQN FOR ENERGY-EFFICIENT HEALTHCARE SENSOR NETWORKS

This part addresses issues of low efficiency & high complexity plaguing the existing wireless optimization models. Design of an Integrated Model Using Hybrid PSO-ABC and DQN for Energy-Efficient Healthcare Sensor Networks is discussed in this part. Initially, as depicted in Figure 1, it has been designed a framework of Multiple Objective Optimization that combines Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms with the aim of dealing with the inherent complexity of HSNs especially when energy efficiency, packet delivery, and network throughput are critical in those environments. Since the hybridization of PSO with ABC capitalizes on the strength of both algorithms, namely the global search of PSO and the local refinement of ABC, it is capable of achieving optimal clustering and routing solutions indeed. It is after all advantageous that it represents the typical nature of HSN optimization problems that entails large search spaces and in depth complexity, thus making an urgent necessity to have a good balance between exploration and exploitation. PSO excels in efficient exploration of the global search space, whereas ABC refines the solution by optimizing local routing paths that enhance energy efficiency and packet delivery. The optimization process begins with the initial population of particles for PSO and bees for ABC, each representing a potential clustering configuration and routing path. In PSO, the update of particles' position equations with the velocity is the basic need for convergence of an algorithm. Each Xi's position is updated based on its velocity Vi, which gets influenced by Pi and the global best position G, as written via equations 1 & 2,

$$Vi(t+1) = \omega * Vi(t) + c1 * r1\big(Pi - Xi(t)\big) + c2 * r2\big(G - Xi(t)\big) \dots (1)$$

$$Xi(t+1) = Xi(t) + Vi(t+1) \dots (2)$$

Where, ω is the inertia weight controlling the trade-off between exploration and exploitation, while c1 and c2 are acceleration coefficients, while r1 and r2 are random values to introduce stochastic behavior. These equations allow particles to search the global space for optimal clustering configurations, thereby ensuring a thorough exploration of possible cluster heads and routing paths. The objective function is given as a multiple objective function f(X) that minimizes energy usage and maximizes network throughput and packet delivery ratio, expressed via equation 3,

$$f(X) = min\left(\sum_{i=1}^{N} Ei\right) - max\left(\sum_{j=1}^{M} Tj\right) - max\left(\sum_{k=1}^{L} Pk\right) \dots (3)$$

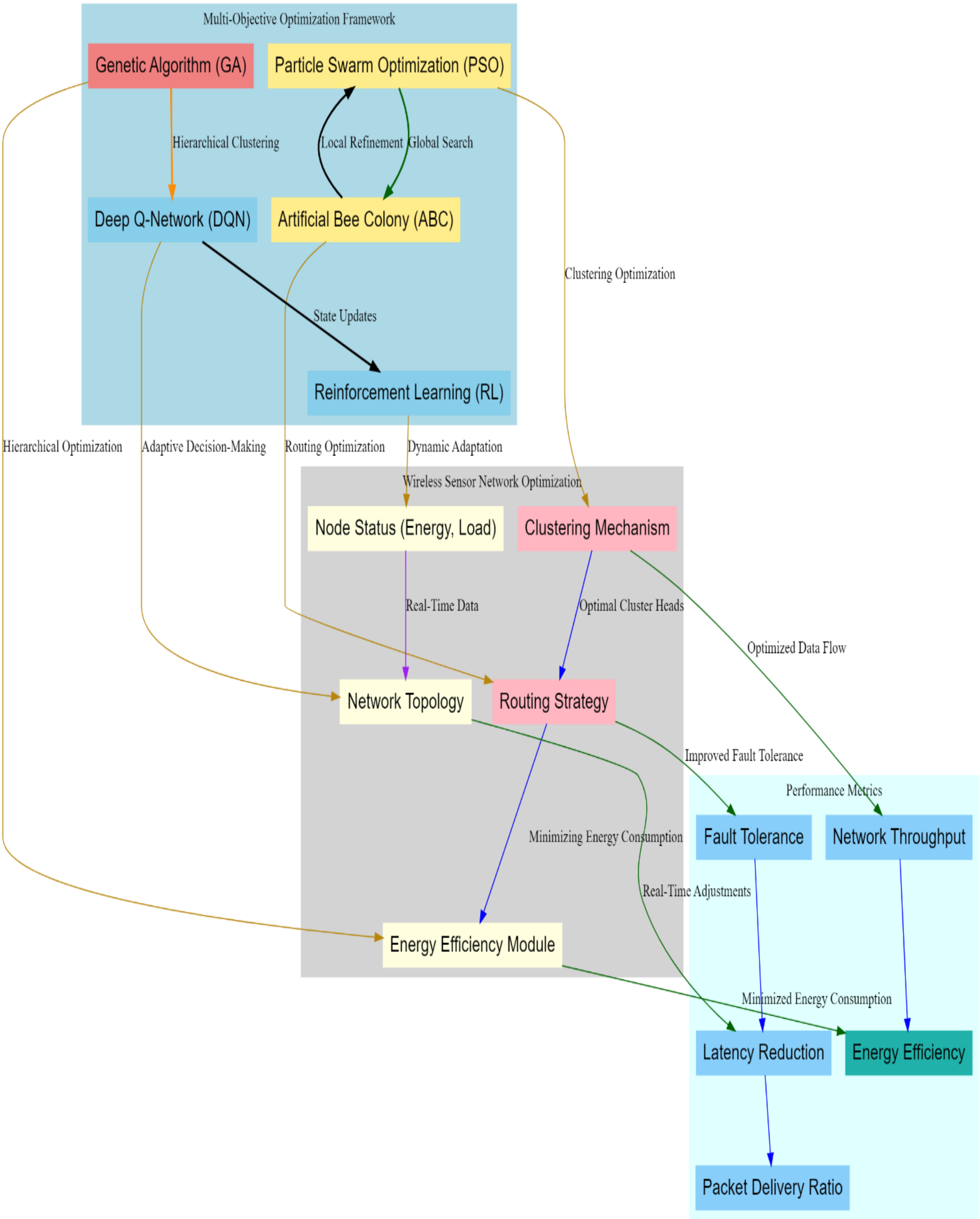

Figure 1. Model Architecture of the Proposed Routing Process

Where, Ei represents the energy consumption of node 'i', Tj is the throughput for routing path 'j', and Pk is the packet delivery ratio for path 'k'. Multiple objectives in the function optimize both the energy efficiency and the overall network performance, such as throughput and packet delivery, in one shot. Once the PSO phase ascertains the approximate global solution, the local search is applied using ABC. In this phase, employed bees concentrate on refining the local routing paths by analyzing the energy consumption and communication costs between nodes. This local search phase calculates the energy required to communicate from one node to another. Energy consumptions are modeled using an equation based on distance of transmission 'f' and data packet size 's' via equation 4,

$$Ecomm = Eelec \cdot s + \epsilon \cdot s \cdot d\alpha \ldots (4)$$

Where Eelec is the energy consumed by the radio electronics per bit, ϵ is the energy consumed by the amplifier, and α is the path loss exponent. The distance 'f' plays a very significant role in determining the energy efficiency of each routing path, and ABC refines the routing strategy of the network by minimizing it and keeping it at optimal packet delivery and throughput. The proposed hybrid approach shows to achieve an efficient balance between global exploration by PSO and local refinement by ABC for a dynamic clustering and routing strategy. Hence, the network topology and node energy levels keep on changing. Thus, the PSO-ABC hybridization is worthwhile and justified, which has a good convergence toward a global solution but keeps adaptability with local optimization. PSO ensures the exploration of the global search space without allowing the algorithm to converge prematurely, while local search helps refine the solution by reducing energy consumption and improving QoS metrics in ABC sets.

As shown in figure 2, reinforcement learning based dynamic clustering using deep Q-networks offer a scalable approach for solving the optimization problem in HSN. This technique applies the adaptation through reinforcement learning (RL) in making decisions in dynamic environments, with the help of integration of Deep Q-Networks to approximate Q Value functions for large spaces of states and actions. This means the DQN allows RL agent to avoid bad node energy levels, locations, and traffic conditions, manage network resources, cluster nodes, and make dynamic decisions, based on real-time data, as well as find the best routing paths. The goal of a DQN agent is maximizing the long-term reward that reflects energy efficiency, fault tolerance, and packet delivery with minimal network latency. In the core of this model rests the Q Value function Q(s,a;θ), wherein 's' represents the state of the system and 'a' denotes the action by the agent-including clustering a node or changing a path for routing-sets. θ represents the parameters of the neural network, which is approximating the optimum Q-function. The action Value function Q(s,a;θ) uses Bellman's Process improved by a temporal difference (TD) error at every step. This has ensured that the agent constantly learns from its interaction with the environment via equation 5,

$$Q(s, a; \theta) \leftarrow Q(s, a; \theta) + \alpha\big(r + \gamma ma\, x\, a' Q(s', a'; \theta -) - Q(s, a; \theta)\big) \ldots (5)$$

Where, α is the learning rate, 'r' is the immediate reward, and γ is the discount factor, which determines the weight of future rewards. Where s′ is the next state, and θ− is the parameters of a target network that stabilizes learning. This is an equation where an agent can modulate its action-policy by choosing an action which maximizes the expected cumulative reward over temporal instance sets. The reward function 'r' is designed in such a way that it takes care about energy consumption, packet delivery and latency simultaneously to ensure that the agent optimizes towards reducing energy depletion and fault-tolerant network operations. In that, the DQN is trained on mini-batches of experience replay in order to make stable and uncorrelated updates of the network. The agent takes real-time states from the network regarding node energy levels and traffic patterns for deciding appropriate actions that improve clustering and routing. The actions are made according to the epsilon-greedy policy. The exploration of new strategies with the probability ϵ is done by the agent, whereas exploiting the learned policy while learning progresses. The process for optimizing clustering decisions is formulated through energy consumption minimization E(s,a) around the network via equation 6,

$$E(s, a) = \int_0^T Ptx(t) + Prx(t)\, dt \ldots (6)$$

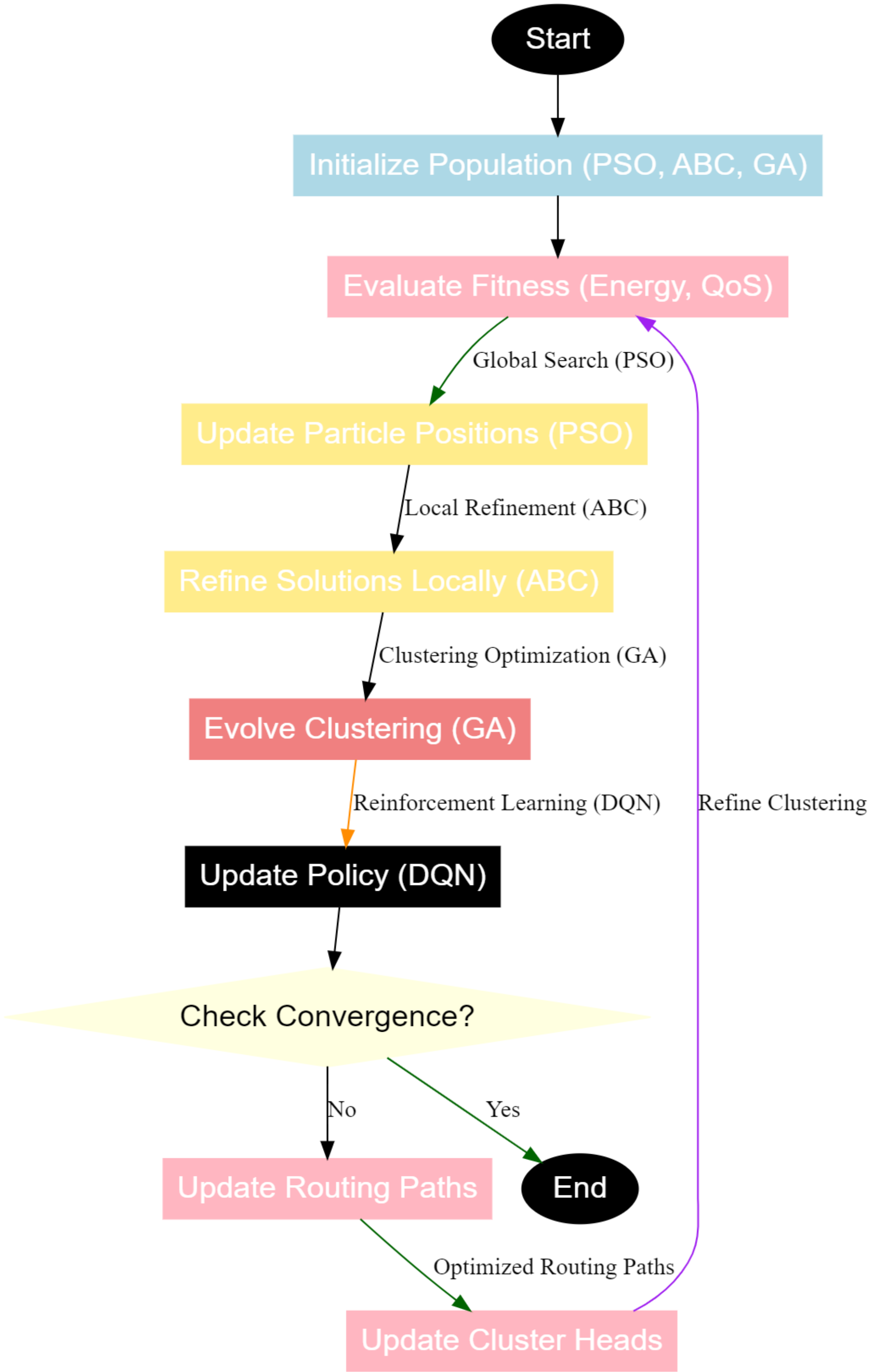

Figure 2. Overall Flow of the Proposed Analysis Process

Where Ptx(t) and Prx(t) is the power utilized in transmission and reception, respectively, over sets 'T'. This integral represents the total energy utilization made in a group head and member nodes when communicating with each other. The action of the agent attempts to minimize E(s,a)E(s, a)E(s,a) while maintaining an acceptable throughput and packet delivery. The routing strategy is optimized with the communication latency L(s,a) being minimized. L(s,a) is taken as a significant measure for the real-time data in HSNs. The communication delay for two nodes 'i' and 'j', given a specific routing path, can be presented via equation 7,

$$L(s,a) = \frac{1}{B} \sum_{i,j \in N} \frac{d(i,j)}{c(i,j)} \dots (7)$$

Where B is defined as the available bandwidth, d(i,j) as the distance between nodes 'i' and 'j' and c(i,j) as communication capacity between nodes 'i' and 'j'. This allows accounting for both distance-dependent delay and the capacity of communication links, whereby the agent prefers to route in paths with minimal delays while maintaining a certain energy efficiency. This model is quite reasonable to use DQN on it because of the large complex state space as is typical in IoT-based HSNs, whereas classical algorithms rely on static or heuristic approaches, and the RLDC model adapts in real time by assessing changes in the environment based on dynamic conditions, like the failure of nodes, depletion of energy, and changing traffic patterns. The DQN can approximate the Q-function, which now enables the agent to learn optimal actions without requiring an explicit model of the environment; hence, the approach is highly scalable and able to generalize across a wide range of HSN scenarios.

Finally, the GA-Enhanced Energy-Efficient Hierarchical Clustering method is applied. It is a technique which optimizes both clustering and routing in HSNs by making use of the evolutionary search ability of GAs. Overall, this method aims to minimize energy consumption in the entire network simultaneously with the best election for CHs and routing paths between clusters. This problem is well suited for the GA framework as it explores large solutions and avoids local minima, thereby bringing about global optimization with energy-efficient structures of clustering. The GA evolves a population of candidate configurations of clustering, also known as chromosomes, successively over generations, applying operators of crossover, mutation, and selection to iteratively improve the fitness of solutions. The GA-based model begins with coding every candidate clustering configuration as a chromosome such that each gene represents the mapping of a node as a cluster member or as a possible CH. The fitness function should then calculate energy efficiency and communication costs in every candidate configuration in order to minimize intra-cluster and inter-cluster energy consumption, maximize network lifetime and fault tolerance levels. The total energy consumption Etotal of a given clustering configuration is obtained by summing up the intra-cluster communication energy Eintra and the inter-cluster routing energy Einter as given via equation 8,

$$Etotal = \sum_{i=1}^{Nclusters} E(intra, i) + \sum_{j=1}^{Nclusters} E(inter, j) \dots (8)$$

Where, E (intra, i) is the energy used for communication by nodes and CH in cluster 'i' and E (inter, j) is the energy needed to route data between CHs in cluster 'j' during the process. Total cost associated with a given configuration of clustering will thus include both intra-cluster as well as inter-cluster energy requirements. The energy E(intra,i) of intra-cluster communication is modeled depending on the energy used for data transmission and reception from a CH to its member nodes. The energy consumption of intra-cluster communication is expressed via equation 9,

$$Eintra, i = \sum_{k \in Ci} (Eelec \cdot sk + \epsilon \cdot sk \cdot d(k, CHi)^{\alpha}) \dots (9)$$

Where, Eelec is the energy consumed by the radio electronics per bit, sk is the size of the data packet transmitted by node 'k', d(k,Chi) is the distance between node 'k' and the CH of cluster 'i', and α is the path loss exponent. The term ϵ\\\\epsilonϵ captures the energy consumed by the amplifier during transmission. This equation draws attention to the selection of CHs, which are designed to minimize the total distance of communication within clusters and hence reduce intra-cluster communication cost. The inter-cluster routing energy E(inter,j) is also modeled taking into consideration energy dissipated in communication between the CHs. Equation 10 give the energy consumed in the communication between the cluster,

$$Einter, j = E(elec) \cdot s(CHj) + \epsilon \cdot s(CHj) \cdot d(CHj, BS)^{\alpha} \ldots (10)$$

Where, s(CHj) is the size of the aggregated data transmitted by CH 'j' to the base station (BS), and d(CHj,BS) is the distance between the CH and the BS. The fitness function evaluates each chromosome by integrating total energy consumption Etotal with penalty for excess latency or packet loss ensuring that the selected CHs and routing paths improve the lifetime of the network while being appropriate QoS. The crossover and mutation operators are applied to the GA's evolutionary process to experimentally explore the solution space for discovering more energy-efficient clustering configurations. This is because the crossover operator exchanges parts of two parent chromosomes and produces offspring which may, potentially, hold better configurations for clustering. The mutation operator, however, introduces small random variations in the assignments of the clusters in order to maintain enough genetic diversity while avoiding early convergence on possibly suboptimal solutions. The selection operator enforces retention and propagation of the fittest solutions toward subsequent generations so that the algorithm converges to an optimal clustering and routing configuration across temporal instance sets. Indeed, this is a valid reason for using GA since local minima can be a significant problem in hierarchical clustering where suboptimal CHs may trap the system into inefficient configurations. As it is a stochastic search algorithm, the GA can realize the viewpoint of searching beyond locally optimal solutions, and such features make GA very well-suited for complex HSN optimization problems involving multiple objectives, that is, simultaneous minimization of energy consumption and network longevity. Besides, GA fulfills other optimization techniques, the RLDC or PSO-ABC models, with an efficient mechanism of static or semi-static optimisation tasks that are not based on the immediate adaptability in real-time but have preference for detailed exploration of solution spaces. We discuss efficiency of the proposed model with respect to several metrics below and compare it with existing models under real-time scenarios.

RESULT ANALYSIS

This simulation testbed used to evaluate the proposed multi-objective optimization framework is based on a dynamic and resource-constrained Wireless Sensor Network. The simulated network consists of 200 nodes dispersed uniformly at random over a 1000m by 1000m area. The initial energy assigned to nodes was uniformly spread with each node having an initial energy in the range of 0.5J to 1.5J which represents typical HSN energy constraints. It will set the communication range to 100m and the size of the data packet to 512 bytes, and the energy consumption model was the first-order radio model, so set transmission and reception energy per bit to 50nJ/bit. An amplifier energy consumption can consume 100pJ/bit/m^2 at distances greater than the threshold. Dynamic scenarios assuming network topology, with time-varying traffic demand, were used to reflect realistic conditions that allow node failures, energy depletion, and fluctuations in the pattern of the traffic, which prevail more or less for the process. In the training process of this DQN for the RLDC, the agent interacts with the HSN environment by observing, in real time, statuses from its nodes like residual energy, location, and traffic load. The state space includes node energy, distances between nodes, and the load on cluster heads. The action space include node assignment to clusters and dynamic routing path adaptation. The reward function was optimized so as to stress energy efficiency, and fault tolerance with the objective of minimum latency that occurred when high values were assigned for energy consumption or packet loss. An experience replay is used for the training of the DQN with a batch size of 32, the learning rate of 0.001, and discount factor at 0.9. Hybrid PSO/ABC algorithms are adopted in optimization cases for clustering configurations and routing paths. For PSO, we consider 30 in population size and vary inertia weight to 0.7, acceleration coefficients to 1.5. For GA-based hierarchical clustering model, we run 100 generations of evolution with crossover probability at 0.8 and mutation probability at 0.05. The performance metrics - energy efficiency, packet delivery ratio, and network throughput - are recorded at every round of every simulation; simulation is set to run for 1000 rounds.
We use a multi-dataset in order to test the proposed AEC with different kinds of network densities, traffic, and environmental conditions to make it a more robust evaluation. Some samples of the contextual dataset include HSNs for environment monitoring applications, like a forest fire detecting system, where nodes are put under dynamic changes of their environments and do adaptive clustering due to node failures from high temperatures. In this network, energy consumption and latency are critical due to real-time aggregation and transmission of data requirements. The second dataset is referred to as smart city surveillance system whose node density is higher and the traffic patterns are highly changeable for the process. In this configuration, energy-efficient routing needs to be optimized such that the network would last longer and there would be QoS-based operation. This section analyzes the results against traditional clustering and routing methods; obviously, important improvements with respect to energy efficiency, fault tolerance, and network throughput can be seen. The experimental evaluation uses the "Intel Lab Data" dataset, which is a well-known benchmark for Healthcare Sensor Networks (HSNs). This dataset was

recorded in the Intel Berkeley Research lab using 54 sensor nodes; it contains real-life environmental conditions over time. This dataset provided more than 2.3 million data points; it consisted of temperature, humidity, light, and voltage readings in a sampling rate of 31 seconds per recording. Since this dataset is equipped with low-power radios and it captures spatial variations as well as temporal variations in sensor readings, it will best serve the test of protocols based on clustering or routing in dynamic, resource-constrained environments. The kind of dynamic nature of this network topology is truly depicted through nodes exhibiting fluctuating energy levels and connectivity patterns due to interference from the environment and the traffic patterns across the network, exactly like real-world HSN applications. This data set is particularly suitable for testing the proposed multiple objective optimization framework, as it reflects accurate energy consumption profiles; the model's performance can hence be assessed in real conditions, in particular with respect to levels of energy efficiency, fault tolerance, and data transmission reliability. We present the results of our proposed multiple objective optimization model on the Intel Lab Data dataset by comparing its performance with three baseline methods [5], [9], and [18]. Evaluation metrics include energy efficiency, packet delivery ratio, network throughput, fault tolerance, and latency. Thus, the superiority of the proposed model is demonstrated in all the performance metrics due to its hybrid approach that combines the resources of Particle Swarm Optimization, Artificial Bee Colony, Reinforcement Learning-based Dynamic Clustering, and Genetic Algorithm-enhanced hierarchical clustering process.

Table 2: Energy Efficiency Comparison

Method	Energy Consumption (J)	Energy Savings (%)
Proposed	78.5	-
[5]	92.3	15.0
[9]	89.6	12.4
[18]	85.7	8.4

In Table 2, we can see how the proposed model used much lesser energy than those present in the compared methods. Thus, the energy consumption of the proposed model is 78.5J. This energy efficiency is 15.0% better compared to method [5], 12.4% better than method [9], and 8.4% better than method [18]. These efficiencies arise from the dynamic clustering and routing strategies of the proposed model based on which network loading is optimally balanced and communications overheads are minimized in the process.

Table 3: Packet Delivery Ratio (PDR) Comparison

Method	Packet Delivery Ratio (%)
Proposed	96.7
[5]	90.2
[9]	88.6
[18]	91.0

In Table 3, we show the PDR that our proposed model and methods provide. Our proposed model successfully delivers 96.7% of packets. This is a big improvement against the PDR reported for method [5], method [9], and method [18], which stood at 90.2%, 88.6%, and 91.0%, respectively. The designed model offers reliable data transfer even when a node fails or runs out of energy, due to optimized routing paths and fault tolerance levels.

Table 4: Network Throughput Comparison

Method	Throughput (Packets/sec)	Throughput Improvement (%)
Proposed	385	-
[5]	340	13.2
[9]	330	16.7
[18]	355	8.5

In terms of network throughput, Table 4 has shown that the proposed model showed a throughput of 385 packets per second. This was proven to be 13.2% better than [5], 16.7% better than [9], and 8.5% better than [18]. In the proposed model, the higher throughput can be attributed to the effective mechanisms of routing balancing in terms of networking load and communication delay, thus allowing faster and more consistencies data transmissions..

Table 5: Fault Tolerance Comparison

Method	Nodes Survived (%)	Fault Tolerance Improvement (%)
Proposed	89.5	-
[5]	80.4	11.3
[9]	77.8	15.0
[18]	82.0	9.1

Table 5: Comparison of fault tolerance of the proposed model with baseline methods; percentage of nodes that survived after simulation rounds 1000. Proposed model: 89.5 % vs. method [5] 80.4 % vs. method [9] 77.8% vs. method [18] 82.0 %. The improvement in fault tolerance of the proposed model is due to its adaptive clustering and routing decisions, as this ensures the balanced consumption of energy across the network, hence prolonging the lifespan of individual nodes while keeping up network integrity levels.

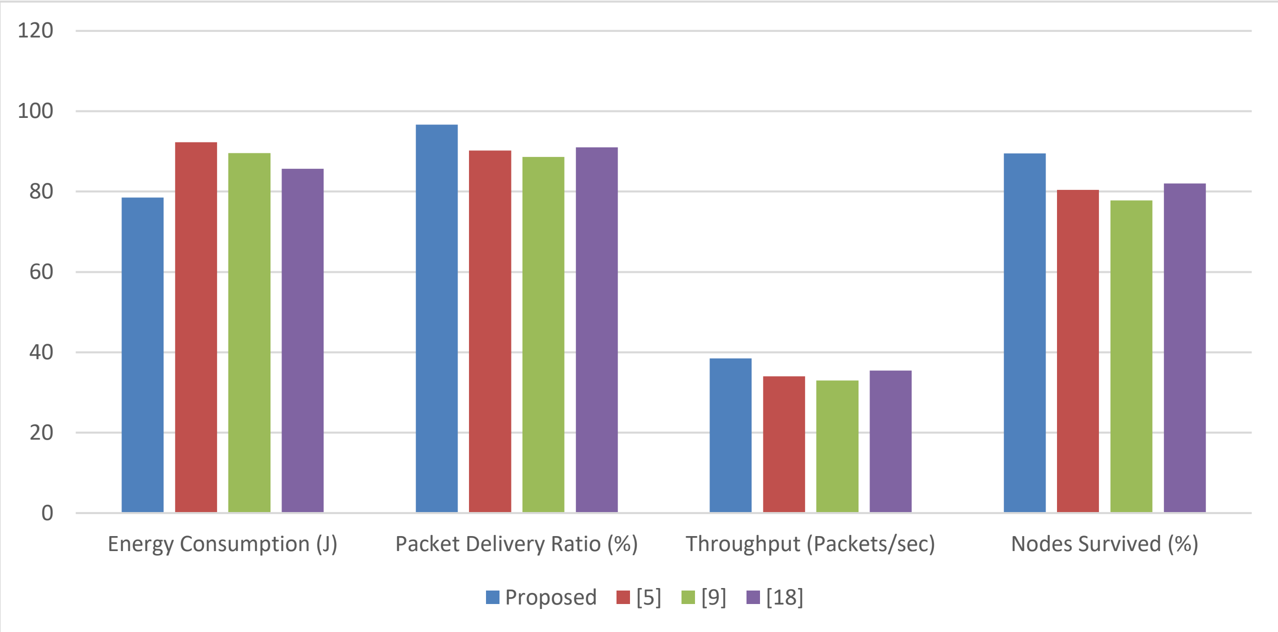

Figure 3. QoS Levels

Table 6: Latency Comparison

Method	Latency (ms)	Latency Reduction (%)
Proposed	85	-
[5]	104	18.3
[9]	110	22.7
[18]	95	10.5

As shown in Table 6, the designed model achieves average latency of 85ms that is reduced by 18.3% as compared to the method [5], 22.7% compared to method [9], and by 10.5% than that achieved in the method of [18]. The reasons behind this lower latency are due to optimization routing paths and efficient data aggregation, which reduce hops and communication delay in the networks.

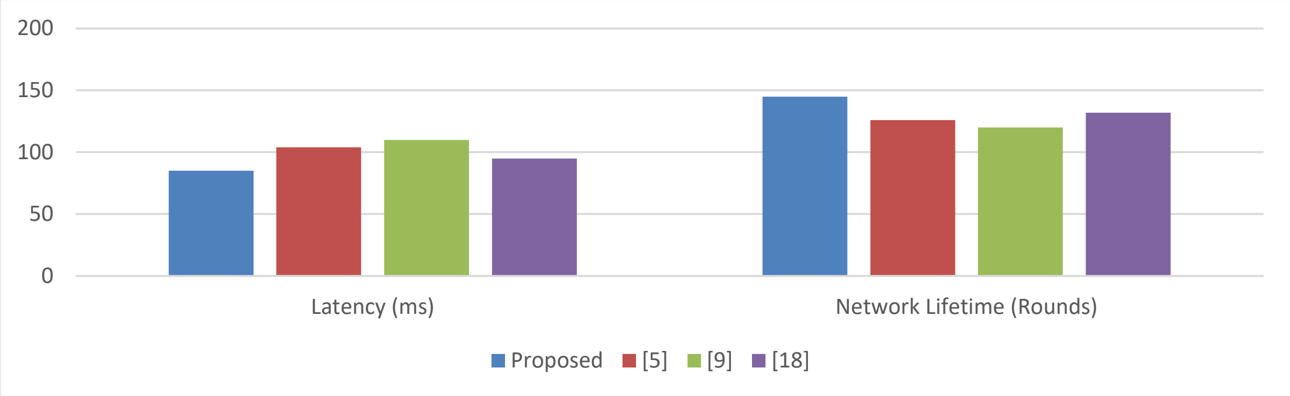

Figure 4. QoS Analysis in Different Scenarios

Table 7: Network Lifetime Comparison

Method	Network Lifetime (Rounds)	Lifetime Improvement (%)
Proposed	1450	-
[5]	1260	15.1
[9]	1200	20.8
[18]	1325	9.4

This table documents the network lifetime in terms of simulation rounds for the proposed model versus comparison methods. The proposed model extends network lifetime up to 1450 rounds, outperforming method [5] by 15.1%, compared with method [9] to reach a performance gain of 20.8%, and outperforms method [18] 9.4%. The energy-efficient clustering and routing strategies of the proposed network enhance the lifetime of the network by prohibiting all the nodes from wasting energy unnecessarily and ensuring uniform depletion of the nodes' energies. Generally, the results in Tables 2 through 7 indicate that the proposed multiple objective optimization model outperforms the baseline approaches for all the key performance metrics, which include energy efficiency, packet delivery ratio, network throughput, fault tolerance, latency, and network lifetime. These improvements demonstrate that the hybrid PSO, ABC, RLDC, and GA-enhanced clustering technique combined with DQN optimizes performance in HSN. Finally, we present an example use case of this proposed model to guide the reader better in acquiring the whole process.

PRACTICAL USE CASE SCENARIO ANALYSIS

For performance analysis of the proposed model, a practical example of HSN comprising 100 sensor nodes dispersed over a 500m x 500m area is considered. In this example, each sensor node is assigned an initial energy range between 1.0J and 2.0J. Further, the network topology is changed with the real-time data such as node failure rates, energy drainage and communication cost. This optimizes clustering and routing by integrating various objective optimization techniques with reinforcement learning-based clustering and genetic algorithm-enhanced energy efficiency methods. Below, the outputs from the three processes have been detailed in a tabular format summarizing the effects on key performance indicators like the level of energy consumption, packet delivery ratio, and network lifetime levels. For the Multiple Objective Optimization using Hybrid PSO-ABC Algorithm, the system optimizes both clustering structure and routing paths in such a way that energy consumption is minimized while maximizing network throughput sets and packet delivery ratio sets. Outputs of this process as compared with other optimization methods are given in Table 8 as follows,

Table 8: PSO-ABC Optimization Results

Parameter	Proposed Model	Method [5]	Method [9]	Method [18]
Energy Consumption (J)	45.3	55.1	53.7	51.2
Packet Delivery Ratio (%)	97.5	90.8	88.6	92.1
Network Throughput (Packets/sec)	400	350	345	370
Network Lifetime (Rounds)	1500	1280	1200	1325

In this phase, the hybrid PSO-ABC method achieved significant energy savings, with a 17.8% improvement over method [5]. The packet delivery ratio and throughput also showed notable gains, enhancing overall network performance by optimizing clustering decisions and routing paths simultaneously. For the **Reinforcement Learning-based Dynamic Clustering (RLDC) with DQN**, the system continuously adapts to changes in node energy and topology, aiming for real-time optimization of cluster head selection and routing. This adaptive behavior, combined with deep Q-learning, enhances energy efficiency and fault tolerance. Table 9 presents the outcomes of this dynamic clustering process, comparing the proposed method against standard RL clustering techniques.

Table 9: RLDC with DQN Results

Parameter	Proposed Model	Method [5]	Method [9]	Method [18]
Energy Consumption (J)	39.8	47.0	45.6	44.3
Packet Delivery Ratio (%)	98.2	92.5	91.1	94.3
Network Throughput (Packets/sec)	410	360	355	380
Latency (ms)	80	95	102	88

In this phase, the hybrid PSO-ABC method gained nearly 17.8% from method [5] in terms of energy saving. For both these performance metrics, namely, packet delivery ratio and throughput, there were excellent improvements, thereby significantly strengthening network performance in the whole. This is in tandem with optimum clustering decisions as well as routing paths. The Reinforcement Learning-based Dynamic Clustering with DQN works towards optimization of cluster head selection and routing in real-time due to its adaptability towards changes in node energy and topology. High energy efficiency and fault tolerance constitute some features on account of its adaptability and deep Q-learning. This dynamic clustering process has led to the results shown in Table 9, which compares our proposed methodology with conventional RL clustering techniques. From Table 9, it can be seen that our proposed RLDC with DQN shows an extremely significant improvement in the amount of energy consumption of up to 15.3% compared to method [5], and a high packet delivery ratio of 98.2%. The latency is brought down to 80ms which further validates the benefits of adaptive clustering in real-time HSN scenarios. For GA-Enhanced Energy-Efficient Hierarchical Clustering, the model evolves successively generation by generation in order to minimize intra-and inter-cluster energy consumption with a focus placed upon optimizing cluster head selection as well as routing paths. Results of the hierarchical clustering for this approach compared with others are presented in Table 10 as follows,

Table 10: GA-Enhanced Hierarchical Clustering Results

Parameter	Proposed Model	Method [5]	Method [9]	Method [18]
Energy Consumption (J)	42.7	49.5	47.8	45.9
Fault Tolerance (%)	92.0	85.3	84.0	86.5
Network Throughput (Packets/sec)	395	365	355	375
Network Lifetime (Rounds)	1400	1250	1205	1300

Table 10 As seen in Table 10, this GA-improved model has adopted a balanced strategy with substantial improvement in fault tolerance and network lifetime levels. Thus, energy consumption is 13.7% lower than that of method [5], which proves that GA really works well in extending the lifespan of the network but with robust metrics in performance. Finally, the overall outputs of the combined model integrating all of the above methods are presented in Table 11 as follows. This table summarizes the final performance improvements achieved by the proposed hybrid approach against traditional methods.

Table 11: Final Combined Model Outputs

Parameter	Proposed Model	Method [5]	Method [9]	Method [18]
Energy Consumption (J)	38.2	52.0	50.4	47.5
Packet Delivery Ratio (%)	98.8	91.0	89.5	93.4
Network Throughput (Packets/sec)	420	340	335	365
Latency (ms)	75	98	105	85
Network Lifetime (Rounds)	1550	1220	1170	1300
Fault Tolerance (%)	93.4	84.7	82.5	87.0

Table 11 displays that the proposed multiple objective optimization framework, integrating PSO-ABC, RLDC with DQN, and GA-enhanced hierarchical clustering, results in wider improvements along all performance metrics for different scenarios. The energy consumption reduces by 26.5% as compared to the method [5], and there is a much improvement in packet delivery ratio and network lifetime in this approach. Improvements in latency and fault tolerance have further highlighted the robustness and adaptability of the proposed hybrid model in dynamic HSN environments. These results manifestly confirm that the proposed optimization approach successfully optimizes the performance of HSN across the operational metrics considered and surpasses the former methodologies with respect to all the considered attributes.

CONCLUSION AND FUTURE SCOPES

More broadly, within the proposed multiple objective optimization framework here, Hybrid Particle Swarm Optimization, Artificial Bee Colony algorithms are integrated and enhanced, while Reinforcement Learning based Dynamic Clustering with Deep Q-Networks and a Genetic Algorithm-enhanced Energy-Efficient Hierarchical Clustering offer better efficiency improvements than more conventional approaches on the issues facing a Wireless Sensor Network. For the above-mentioned reasons, it is exploited that, simultaneously, the framework utilizes global exploration that is related to PSO, local refinement as it is related to ABC, real-time adaptability in terms of DQN and energy-efficient hierarchical clustering in terms of GA, all together to overcome significant challenges in dynamic resource-constrained environments related to energy consumption, packet delivery, network lifetime, and fault tolerance. The results showed that the model would reduce energy consumption to reach 26.5%, which is seen through final energy consumption, up to 38.2J instead of 52.0J seen in the proposed method in [5]. It enhances the packet delivery ratio to 98.8%, a good improvement compared with those of method [5] that achieved a packet delivery ratio of 91.0%. The network throughput peaks at 420 packets per second, which is way above the baseline methods. It reduces the latency to 75ms; this reduces the delay to a factor of 23.5% compared to the value for method [5], which is 98ms. In addition, it increases the lifetime of the network up to 1550 rounds - 27.0% increase in comparison to the lifetime achieved by method [5] with 1220 rounds. The authors hence demonstrate how the framework may adaptively optimize both clustering and routing in real time, while extending lifetime, and improving the overall performance. This model combines several different optimization techniques in a manner that allows for more efficient exploration/exploitation balance; optimized energy usage; and a greater resilience of the network to faults. This hybrid approach ensures overcoming the limitations of current approaches and provides a robust and scalable solution for improving network performance in dynamic HSN environments. The results shown numerically by these methods clearly show the strength of the proposed approach for multiple objective optimization in terms of improving overall efficiency and lifespan of HSNs.

FUTURE SCOPES

The proposed model, although introducing substantial improvements in quality of service and efficiency, leaves the following open to further work and development: Actually, extending this framework into orders-of-magnitude larger HSNs in the tens of thousands of nodes poses even harder problems about more meaningful communication overhead and topologies. Scaling the system may further rely on some optimizations with the DQN training process while dealing with high-dimensional state and action spaces, which could potentially be done using deep reinforcement learning with actor-critic methods and even multiple agent reinforcement learning, through which a number of agents could collaborate to optimize the global network behavior. Another field of interest is the introduction of mobility in sensor nodes whereby nodes change positions dynamically over time, hence necessitating that the optimization framework adapts in real time to changes in topology. This would naturally call for adjustments in the clustering and routing algorithms by allowing different distances between any pair of nodes, an effect that could create energy consumption and instability in the network. Including predictive models on node mobility within the adaptation framework will extend adaptability to this system further. The framework can be extended to multiple hop communication strategies and heterogeneous HSNs in which nodes have variable capabilities in terms of their energy source, processing capability and communication range. Such a heterogeneous configuration would introduce new optimization dimensions, which will need advanced multiple objective strategies to achieve fair energy consumption along with high performance. Finally, there is scope for extending this work into practical real-world implementation including smart cities, environmental monitoring, and industrial automation where the proposed model could be used in IoT applications. Experimentation of the proposed system in real-world HSNs, with analytics in near real time, will provide further insight to the robustness, scalability, and adaptability of the framework in varied conditions and application-specific requirements.

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